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steam-reviews-ML

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1730 lines (1730 loc) · 173 KB

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Steam Reviews Prediction

In [57]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, precision_score, recall_score, confusi
import matplotlib.pyplot as plt
from sklearn.feature_extraction import text
from sklearn.model_selection import GridSearchCV
from sklearn.dummy import DummyClassifier
from sklearn.ensemble import RandomForestClassifier
```

Business Understanding

The objective of the notebook is to be able to predict whether or not a game will be recommended based off the review. By analyzing reviews, the model identifies key words and phrases that lead to positive or negative recommendations. This can help game developers and marketers understand what aspects of a game are most appreciated by users when creating a sequel or a game in a specific genre.

Data Understanding

The data we will be looking at is a dataset acquired from Kaggle containing Steam reviews from 2017 and before.

> https://www.kaggle.com/datasets/andrewmvd/steam-reviews

The data will be downloaded and placed in the following path: `../data/dataset.csv` . It should be about a 2.6gb file when unzipped.

Now the data will be loaded as `df`

In [2]:
```
df = pd.read_csv('../data/dataset.csv')
```

Sneak peek of the data

In [3]:
```
df.head()
```

Out[3]:

	app_id	app_name	review_text	review_score	review_votes
0	10	Counter-Strike	Ruined my life.	1	0
1	10	Counter-Strike	This will be more of a ''my experience with th...	1	1
2	10	Counter-Strike	This game saved my virginity.	1	0
3	10	Counter-Strike	• Do you like original games? • Do you like ga...	1	0
4	10	Counter-Strike	Easy to learn, hard to master.	1	1

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6417106 entries, 0 to 6417105
Data columns (total 5 columns):
 #   Column        Dtype 
---  ------        ----- 
 0   app_id        int64 
 1   app_name      object
 2   review_text   object
 3   review_score  int64 
 4   review_votes  int64 
dtypes: int64(3), object(2)
memory usage: 244.8+ MB
```

We can see that the data has over 6 million rows with the following structure:

1. `app_id`
   - Game ID
2. `app_name`
   - Game Name
3. `review_text`
   - Review Content
4. `review_score`
   - 1 for recommended, -1 for not recommended
5. `review_votes`
   - number of votes for how helpful the review was

The rows that will be relevant for training the model will be `review_score` and `review_votes` as we just need the content of the review and whether or not it was a positive review.

Data Preparation

We are going to drop NA and duplicate rows.

In [5]:
```
df.dropna(inplace=True)
df.drop_duplicates(inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 4483850 entries, 0 to 6417105
Data columns (total 5 columns):
 #   Column        Dtype 
---  ------        ----- 
 0   app_id        int64 
 1   app_name      object
 2   review_text   object
 3   review_score  int64 
 4   review_votes  int64 
dtypes: int64(3), object(2)
memory usage: 205.3+ MB
```

In [6]:
```
df.reset_index(drop=True, inplace=True)
```

In [7]:
```
df
```

Out[7]:

	app_id	app_name	review_text	review_score	review_votes
0	10	Counter-Strike	Ruined my life.	1	0
1	10	Counter-Strike	This will be more of a ''my experience with th...	1	1

2	10	Counter-Strike	This game saved my virginity.	1	0
3	10	Counter-Strike	• Do you like original games? • Do you like ga...	1	0
4	10	Counter-Strike	Easy to learn, hard to master.	1	1
...	...	...	...	...	...
4483845	99910	Puzzle Pirates	I really ove this game but it needs somethings...	-1	0
4483846	99910	Puzzle Pirates	Used to play Puzzel Pirates 'way back when', b...	-1	0
4483847	99910	Puzzle Pirates	This game was aright, though a bit annoying. W...	-1	0
4483848	99910	Puzzle Pirates	I had a nice review to recommend this game, bu...	-1	0
4483849	99910	Puzzle Pirates	The puzzles in this game are fun, but you have...	-1	0

4483850 rows × 5 columns

Grabbing just the `review_text` and `review_score` into its own dataframe because thats the only information we are concerned with when training this model.

In [8]:

```
data = df[['review_text', 'review_score']]
```

Sampling 5% of the data in order to cut down on the amount of data fed when training to reduce the model training time. To improve accuracy we can increase the sample size.

In [9]:

```
data_sample = data.sample(frac=0.05, random_state=42)
data_sample
```

Out[9]:

	review_text	review_score
2431934	old school!	1
1250528	Game is very fun. It could use some tweeking a...	1
590126	A short emotionally provocative game that tran...	1
2110494	Freedom fall is a short, simple, and very fun ...	1
2527583	I have played the witcher 2 and i can say that...	1
...	...	...
3350267	Larian managed to make the best RPG of the 201...	1
833185	You couldn't pick up a guy at the gay bar Male...	1
3873486	What is this game even? Honestly, no one knows...	1
4126649	Seriously, buy this game. With all of the mod ...	1
4372237	Just... wow. The Blackwell games started so we...	1

224192 rows × 2 columns

In [12]:

```
data_sample.value_counts(['review_score'])
```

Out[12]:
```
review_score
 1     183903
-1      40289
Name: count, dtype: int64
```

Running a train test split on the data with a test size of 0.2

In [13]:
```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(data_sample['review_text'], data_samp
```

Gathering a list of stop words in order to remove them during the TFIDF Vectorizer to cleanup the input of meaningless features.

In [18]:
```
stop_words = list(text.ENGLISH_STOP_WORDS)
```

Using the TFIDF Vectorizer in order to convert text data into numerical data to train the model. Looking at unigrams to trigrams.

In [15]:
```
tfidf = TfidfVectorizer(max_features=5000, stop_words=stop_words, ngram_range=(1,3))
X_train_tfidf = tfidf.fit_transform(X_train)
X_test_tfidf = tfidf.transform(X_test)
```

Modeling

Dummy Model

We are going to create a scores dictionary to keep track of all the scores of each model to compare later.

In [42]:
```
scores = []
```

We create a baseline model with the DummyClassifer to establish a baseline.

In [28]:
```
baseline_model = DummyClassifier(strategy='most_frequent')
baseline_model.fit(X_train_tfidf, y_train)
y_pred_baseline = baseline_model.predict(X_test_tfidf)
print("Baseline Model Performance:")
report = classification_report(y_test, y_pred_baseline)
print(report)
```

```
Baseline Model Performance:
              precision    recall  f1-score   support

          -1       0.00      0.00      0.00      7977
           1       0.82      1.00      0.90     36862

    accuracy                           0.82     44839
   macro avg       0.41      0.50      0.45     44839
weighted avg       0.68      0.82      0.74     44839

/opt/miniconda3/envs/mac_tf/lib/python3.11/site-packages/sklearn/metrics/_classification.p
y:1509: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels wi
th no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/opt/miniconda3/envs/mac_tf/lib/python3.11/site-packages/sklearn/metrics/_classification.p
y:1509: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels wi
th no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
/opt/miniconda3/envs/mac_tf/lib/python3.11/site-packages/sklearn/metrics/_classification.p
y:1509: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels wi
th no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

In [44]:

```
scores.append(['baseline_model', 'precision', precision_score(y_test, y_pred_baseline, av
scores.append(['baseline_model', 'recall', recall_score(y_test, y_pred_baseline, average=
scores
```

```
/opt/miniconda3/envs/mac_tf/lib/python3.11/site-packages/sklearn/metrics/_classification.p
y:1509: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels wi
th no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Out[44]:

```
[['baseline_model', 'precision', 0.4110484176721158],
 ['baseline_model', 'recall', 0.5]]
```

As we can see the model is not great at predicting any negative recommendations and is extremely overfit.

First Model

Next, we are going to create our first model using a Decision Tree with a couple of hyperparameters

In [20]:

```
param_grid = {
    'max_depth': [20],
    'min_samples_split': [10],
    'min_samples_leaf': [5]
}
grid_search = GridSearchCV(DecisionTreeClassifier(random_state=42), param_grid, cv=5, ver
grid_search.fit(X_train_tfidf, y_train)
```

```
Fitting 5 folds for each of 1 candidates, totalling 5 fits
[CV 1/5] END max_depth=20, min_samples_leaf=5, min_samples_split=10;, score=0.843 total ti
me=   7.5s
[CV 2/5] END max_depth=20, min_samples_leaf=5, min_samples_split=10;, score=0.842 total ti
me=   7.3s
[CV 3/5] END max_depth=20, min_samples_leaf=5, min_samples_split=10;, score=0.846 total ti
me=   7.6s
[CV 4/5] END max_depth=20, min_samples_leaf=5, min_samples_split=10;, score=0.843 total ti
me=   7.6s
[CV 5/5] END max_depth=20, min_samples_leaf=5, min_samples_split=10;, score=0.841 total ti
me=   7.7s
```

Out[20]:

```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(random_state=42),
             param_grid={'max_depth': [20], 'min_samples_leaf': [5],
                         'min_samples_split': [10]},
             verbose=3)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Grabbing the best combination for the Decision Tree Model from the GridSearch

In [21]:

```
best_tree_model = grid_search.best_estimator_
```

And now that we have the best decision tree model we are going to evaluate the model's performance

In [46]:

```
y_pred_tree = best_tree_model.predict(X_test_tfidf)
print("Tuned Decision Tree Model Performance:")
print(classification_report(y_test, y_pred_tree))
```

```
Tuned Decision Tree Model Performance:
              precision    recall  f1-score   support

          -1       0.67      0.27      0.38      7977
           1       0.86      0.97      0.91     36862

    accuracy                           0.85     44839
   macro avg       0.76      0.62      0.65     44839
weighted avg       0.83      0.85      0.82     44839
```

In [47]:

```
scores.append(['decision_tree', 'precision', precision_score(y_test, y_pred_tree, average
scores.append(['decision_tree', 'recall', recall_score(y_test, y_pred_tree, average='macr
scores
```

Out[47]:

```
[['baseline_model', 'precision', 0.4110484176721158],
 ['baseline_model', 'recall', 0.5],
 ['decision_tree', 'precision', 0.7632120683261521],
 ['decision_tree', 'recall', 0.6183076212539242]]
```

As we can see the model here can actually predict negative recommendations however it still can be seen as overfit and way better at predicting positive recommendations than negative ones.

Second Model

The next model I wanted to try is a Random Forest Classifier due to it's strength in handling imbalanced data better than simple Decision Trees and better insights on feature importance.

In [19]:

```
# Train the Random Forest model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_tfidf, y_train)
```

```
Random Forest Model Performance:
              precision    recall  f1-score   support

          -1       0.77      0.41      0.54      7977
           1       0.88      0.97      0.93     36862

    accuracy                           0.87     44839
   macro avg       0.83      0.69      0.73     44839
weighted avg       0.86      0.87      0.86     44839
```

In [48]:

```
# Evaluate the model
y_pred_rf = rf_model.predict(X_test_tfidf)
print("Random Forest Model Performance:")
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Model Performance:
              precision    recall  f1-score   support

          -1       0.77      0.41      0.54      7977
           1       0.88      0.97      0.93     36862

    accuracy                           0.87     44839
   macro avg       0.83      0.69      0.73     44839
weighted avg       0.86      0.87      0.86     44839
```

In [49]:

```
scores.append(['random_forest', 'precision', precision_score(y_test, y_pred_rf, average='
scores.append(['random_forest', 'recall', recall_score(y_test, y_pred_rf, average='macro'
scores
```

Out[49]:

```
[['baseline_model', 'precision', 0.4110484176721158],
```

```
 ['baseline_model', 'recall', 0.5],
 ['decision_tree', 'precision', 0.7632120683261521],
 ['decision_tree', 'recall', 0.6183076212539242],
 ['random_forest', 'precision', 0.828494685755017],
 ['random_forest', 'recall', 0.6933605324820007]]
```

Evaluation

Now we are going to compare the scores of each of the models and determine which one was the most successful and if it successful enough to be deployed.

In [50]:

```
scores_df = pd.DataFrame(scores, columns=['Model', 'Metric', 'Score'])
scores_df
```

Out[50]:

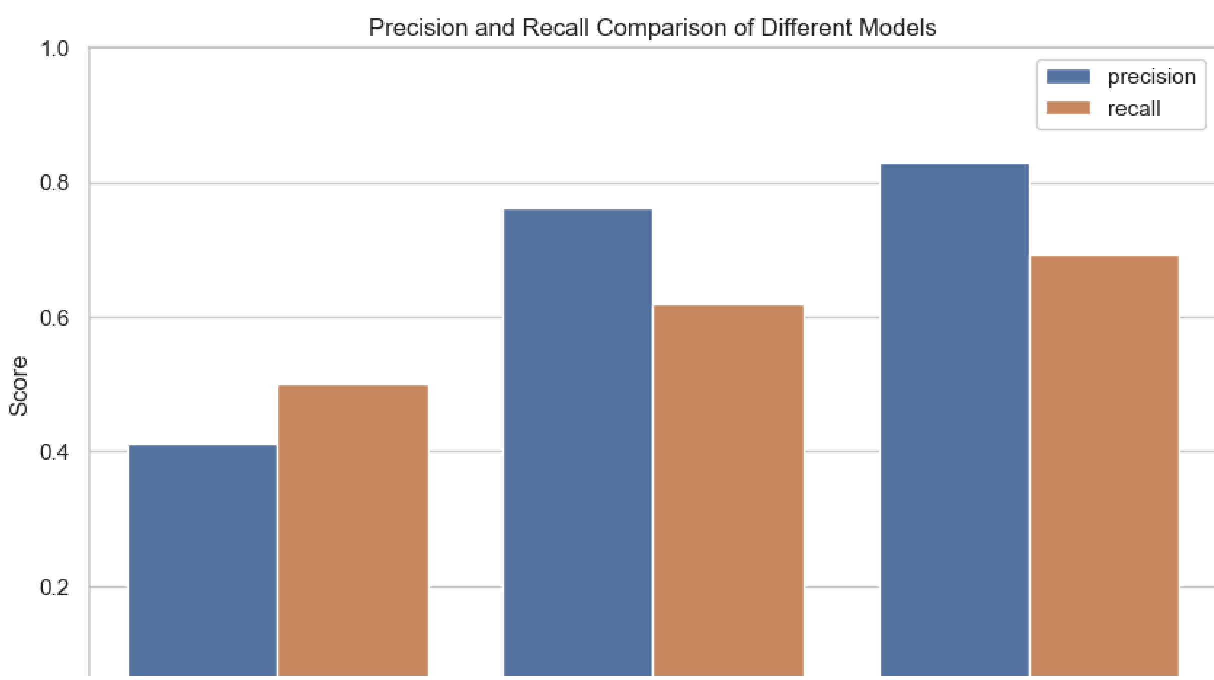
	Model	Metric	Score
0	baseline_model	precision	0.411048
1	baseline_model	recall	0.500000
2	decision_tree	precision	0.763212
3	decision_tree	recall	0.618308
4	random_forest	precision	0.828495
5	random_forest	recall	0.693361

In [53]:

```
# Create a bar plot
plt.figure(figsize=(10, 6))
sns.barplot(x='Model', y='Score', hue='Metric', data=scores_df)

# Add titles and labels
plt.title('Precision and Recall Comparison of Different Models')
plt.xlabel('Model')
plt.ylabel('Score')
plt.ylim(0, 1)

# Show the plot
plt.legend(loc='upper right')
plt.show()
```



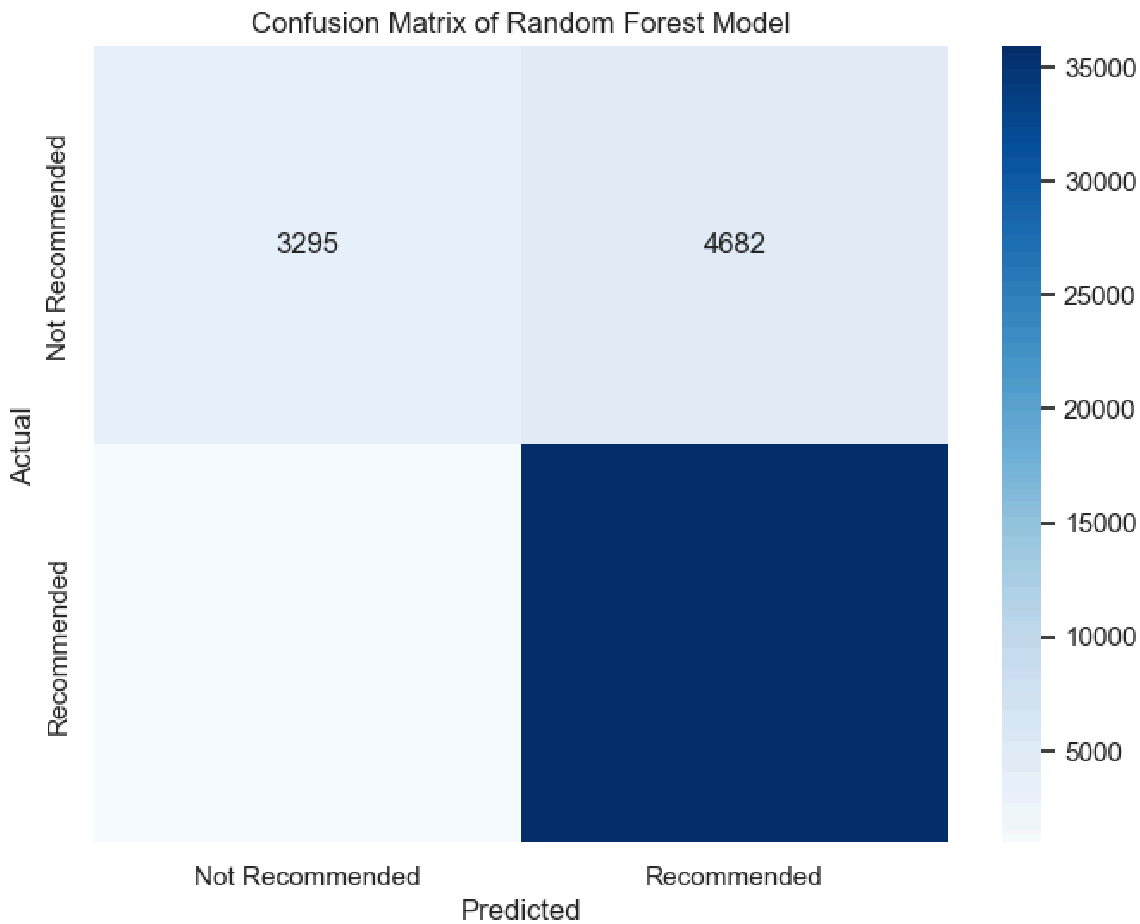
After training the model and retrieving the classification report, we can see that the **Random Forest Classifer** is a clear improvement to the previous two models due to its near 10% increase in precision on negative recommendations and near 20% increase on the recall while still maintaining very high values for the positive recommendations.

Let's take a look at a confusion matrix of the **Random Forest Classifier** to showcase the precision

In [58]:

```
conf_matrix = confusion_matrix(y_test, y_pred_rf)

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Not Recommendec
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix of Random Forest Model')
plt.show()
```



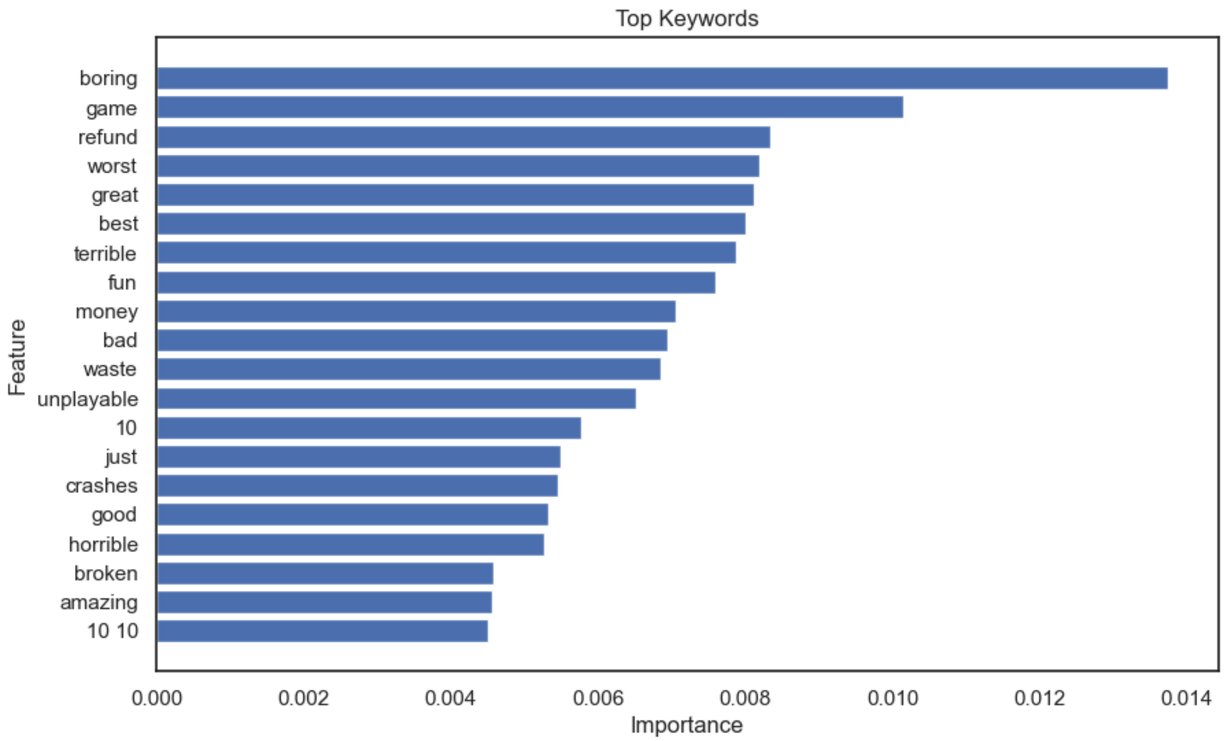
Because the best model was concluded as the random forest we are going to look at the model's feature importances to deduce which words or phrases made the most impact in determining whether or not a review is positive.

In [56]:

```
# Feature importance
feature_names = tfidf.get_feature_names_out()
importance = rf_model.feature_importances_
feature_importance = pd.DataFrame({'feature': feature_names, 'importance': importance})
```

```
feature_importance = feature_importance.sort_values(by='importance', ascending=False)

# Plot top keywords
top_features = 20
plt.figure(figsize=(10, 6))
plt.barh(feature_importance['feature'][:top_features], feature_importance['importance'][:
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title('Top Keywords')
plt.gca().invert_yaxis()
plt.show()
```



We can see that not many phrases were recognized as important features but it's likely due to the small sample of data that was fed through the model. Additionally, we can see arguable stop words also contributing to the importance such as 'just'. This is something to look out for in the future as the model should still be further trained with hyperparameters in effect and more training data being sent through.

Using the random forest model we can feed in a 'custom' review and have the vectorizer transform it for us and sent to the model to predict whether or not the review is positive or not.

In [53]:

```
# Example new review
new_review = ["waste i hated it"]

# Transform the new review
new_review_tfidf = tfidf.transform(new_review)

# Make prediction using the best model (assuming best_model is already defined and traine
prediction = rf_model.predict(new_review_tfidf)
print(prediction)

# Interpret the prediction
if prediction[0] == 1:
    print("The model predicts: Recommended")
else:
    print("The model predicts: Not Recommended")
```

```
[-1]
The model predicts: Not Recommended
```

I want to emphasize that the beauty in this project is not necessarily the model predicting yay or nay but in the features that can be identified as important for either direction. Game developers can look at this newly organized data when pursuing the creation of a new game to find what is something that is sought after in games of a specific name or genre.

Although the model was mostly successful in predicting yay or nay, we want to further reduce the false positives that are returned by the model. However, it is worth noting that the current behavior is preferred to underfitting due to the users of this model wanting to further focus on what is positive and good for a game rather than the negative because by doing what is desired you avoid what is undesired.

Next Steps:

The model can always be further improved but the real next steps to be accomplished before deployment is further honing in on the features that contribute to positive reviews and categorizing them for specific